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DECENTRALIZED AUTONOMOUS FAULT DETECTION IN WIRELESS STRUCTURAL HEALTH MONITORING SYSTEMS USING STRUCTURAL RESPONSE DATA

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Abstract. *Sensor faults can affect the dependability and the accuracy of structural health monitoring (SHM) systems. Recent studies demonstrate that artificial neural networks can be used to detect sensor faults. In this paper, decentralized artificial neural networks (ANNs) are applied for autonomous sensor fault detection. On each sensor node of a wireless SHM system, an ANN is implemented to measure and to process structural response data. Structural response data is predicted by each sensor node based on correlations between adjacent sensor nodes and on redundancies inherent in the SHM system. Evaluating the deviations (or residuals) between measured and predicted data, sensor faults are autonomously detected by the wireless sensor nodes in a fully decentralized manner. A prototype SHM system implemented in this study, which is capable of decentralized autonomous sensor fault detection, is validated in laboratory experiments through simulated sensor faults. Several topologies and modes of operation of the embedded ANNs are investigated with respect to the dependability and the accuracy of the fault detection approach. In conclusion, the prototype SHM system is able to accurately detect sensor faults, demonstrating that neural networks, processing decentralized structural response data, facilitate autonomous fault detection, thus increasing the dependability and the accuracy of structural health monitoring systems.*

1 INTRODUCTION

Structural health monitoring (SHM) systems can be deployed to evaluate the conditions and to ensure the structural integrity of civil engineering structures. To eradicate problems related to cost and installation time in conventional wired SHM systems, wireless sensor nodes are employed. An advantage of wireless sensor nodes is the collocation of processing power with sensing modules; hence, embedded computing can be employed to perform a variety of SHM tasks. Over their lifetime, the wireless sensor nodes can become inaccurate, faulty, or may even break. To ensure the dependability and the accuracy of the SHM system, and the integrity of the structure, sensor faults must be reliably detected in real time [1].

For sensor fault detection, artificial neural networks (ANN) have been used in several engineering diciplines. Smarsly and Law (2014), for example, have proposed the use of ANNs for sensor fault detection by utilizing the analytical redundancy in the correlations between sensor outputs [2]. Obst (April 2009) has presented a distributed recurrent neural network with local communication to detect sensor faults [3]. Basirat and Khan (June 2009) have introduced a neural network approach to distinguish accurate sensor data from faulty sensor data [4]. Yuen and Lam (2006) have presented a method to develop ANN designs for damage detection in structural health monitoring [5]. Venkatasubramanian et al. (1990) have tested various neural network topologies for detecting process failures, such as sensor faults [6].

In this paper, a wireless SHM system with decentralized, autonomous fault detection, producing minimal wireless transmission, is presented. One ANN is embedded into each sensor node and trained to autonomously detect sensor faults by comparing measured data with predicted data. To this end, the measured data collected from the structure is transformed into the frequency domain, and correlated Fourier amplitudes from different sensor nodes at selected frequencies are fed to each ANN. By using only Fourier amplitudes at selected peaks of the frequency spectrum, corresponding to natural frequencies of the structure, a significant reduction in wireless data transmission and storage is achieved. The ANNs are optimized for the test structure used in this study, enabling efficient and accurate sensor fault detection.

In the first part of the paper, background information on sensor fault detection using artificial neural networks is given, followed by a description of the mode of operation of the proposed SHM system. In the second part of the paper, the implementation of the SHM system is shown, and laboratory experiments, devised to validate the SHM system, are presented. Several topologies and modes of operation of the embedded ANNs are tested with simulated sensor faults. The performance of the ANNs is investigated with respect to the dependability and the accuracy of the fault detection approach, the results are discussed and an optimal configuration for the presented test structure is defined. The paper concludes with a summary and a brief outlook on future work directions.

2 SENSOR FAULT DETECTION USING ARTIFICIAL NEURAL NETWORKS

The following section gives a brief overview of sensor fault detection associated with artificial neural networks, and shows the general architecture of the proposed SHM system.

A well-known approach towards fault detection is the installation of physically redundant sensors. Faulty sensors can be identified through the deviation of their measurements from the measurements of correlated sensors. Physical redundancy, although efficient for sensor fault detection, causes increased installation and maintenance costs due to multiple installations of sensors. Representing a more efficient approach, analytical redundancy typically uses mathematical functions, mapping the characteristics of the structure and the correlations of the installed sensors [7]. Specifically, virtual sensor measurements are computed for each sensor and then compared to the actual measurements. If the properties of a structure are known, physics-based models, e.g. finite element models, can be used in combination with data from adjacent sensor nodes to predict measurements of a sensor. However, to use numerical models, a priori knowledge about the structure is required.

Without a priori knowledge, analytical redundancy can be implemented on wireless sensor nodes based on data-driven models, such as artificial neural networks. ANNs are a class of algorithms that are inspired by biological nervous systems, such as the human brain. ANNs are used to approximate non-linear functions through adaptation to given data sets. Applications of ANNs are used in several areas, i.a. cancer detection, pattern recognition in image analysis, and sensor fault detection.

As depicted in Figure 1, ANNs essentially consist of interconnected data processing units, called "artificial neurons" [8]. Usually, the neurons are grouped in different layers: one input layer, one output layer, and one or more hidden layers. The connections between the neurons, termed "synapses", have adaptive weights according to the connection strength between two neurons. The connections are used for data exchange between the neurons: the output of the neurons of one layer is used as the input of the neurons of the next layer. ANNs adapt to different applications by learning. Progress in learning is achieved by adjusting the weights of the synapses until a set of given input values results in the desired output values. ANNs can be customized to various objectives by using different topologies, neuron functions, and learning strategies [9].

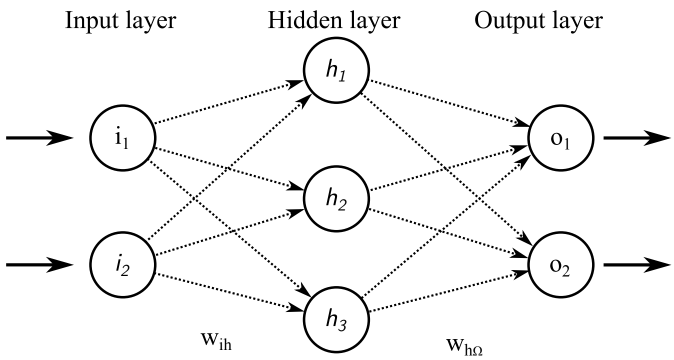

Figure 1: Example for an artificial neural network with two input neurons, two hidden neurons and two output neurons, connected by synapses

The SHM system prototype proposed in this study consists of wireless sensor nodes and a host computer, both linked through a base station. The components of the SHM system perform different tasks, as shown in the data flow in Figure 2. During system operation, the sensor nodes collect acceleration response data. The fundamental frequency as well as the corresponding Fourier magnitude of the acceleration response data of the structure are estimated by the sensor nodes using the fast Fourier transform (FFT) and a peak picking algorithm. For decentralized sensor fault detection, a distinct artificial neural network is embedded into each sensor node. In the ANN, the output of a sensor node is represented either by the input of an input neuron or by the output of an output neuron. The predicted magnitude of a sensor node, used for decentralized fault detection, is returned as output, the calculated magnitudes of neighbor sensor nodes are used as input. The processed data is transmitted wirelessly to the base station and then to the host computer. On the host computer, the data is stored in a MySQL database. Additional diagnostics and information retrieval are conducted on the host computer in further steps.

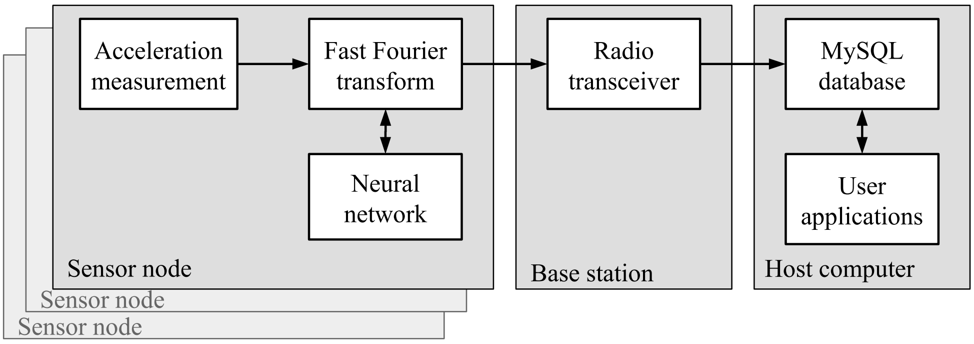

Figure 2: Hardware components and dataflow of the proposed SHM system

3 IMPLEMENTATION AND VALIDATION OF THE PROTOTYPE SHM SYSTEM

In this section, the implementation of the proposed SHM system is described. Laboratory experiments, devised to validate the SHM system, are presented and the test results are discussed.

3.1 Implementation

The proposed SHM system is implemented in an object-oriented way using the Java programming language. The sensor nodes and the base station are of type “Oracle Sun SPOT”. The main board of the Sun SPOTs features a 400 MHz ARM main processor, 1 MB of memory, 8 MB of flash memory and an IEEE 802.15.4 radio transceiver. The application board contains a 3-axis digital output accelerometer, an ambient light sensor, a temperature sensor, and eight tricolor LEDs. The accelerometer ranges between $\pm$ 2 g and $\pm$ 8 g and has a maximum sampling rate of 125 Hz [10].

3.2 Laboratory experiments

To validate the fault detection approach, the sensor nodes are installed on a test structure, as shown in Figure 3. The test structure is a 4-story frame structure consisting of steel plates of 25 cm $\times$ 50 cm $\times$ 0.75 mm. The plates are mounted on threaded rods with a vertical clearance of 23 cm. At the bottom of the structure, the rods are fixed into a solid block of 40 cm $\times$ 60 cm $\times$ 30 cm. The SHM system is installed on the test structure by mounting one wireless sensor node in the middle of story 3 and story 4, and two sensor nodes on story 2, one in the middle and one shifted aside by 20 cm.

In several test runs, the structure is excited by deflecting the top story. A test run includes a training phase and a data collection phase, each performed simultaneously on every sensor node. The training phase of the SHM system consists of the implementation and the training of an artificial neural network. The training of the ANN is completed through several sampling events used as training input. A sampling event includes the excitation of the structure, sampling of 512 acceleration measurements, on-board estimation of the fundamental frequency and corresponding Fourier magnitude, and wireless data exchange with the other sensor nodes. The data collection phase consists of any desired number of sampling events, sensor fault detection,

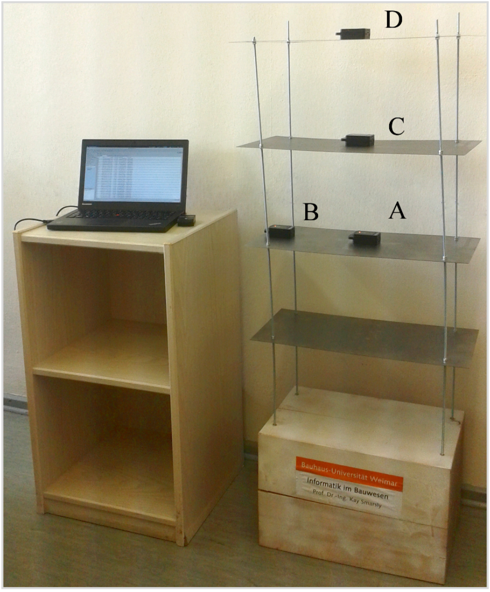

Figure 3: Instrumentation of the test structure

and data storage. After every sampling event, the predicted magnitude of each sensor node is predicted by using the measured magnitudes of the other sensor nodes as input to the neural network. The deviation of the measured magnitude and the predicted magnitude is calculated by the sensor node. A deviation exceeding a threshold is indicative of a sensor fault.

To find a suitable artificial neural network architecture for the laboratory test setup, several different topologies and neuron behaviors are tested offline. Finally, the optimal ANN is embedded into each sensor node to validate the fault detection online. To train and to test the ANNs, 100 test samples are generated. To this end, the test structure is excited and acceleration response data is collected and stored in the database. The acceleration response data is split randomly into 70% of training data and 30% of test data. Then, sensor faults are simulated to validate the autonomous sensor fault detection. For each simulated sensor fault, 30 test cases are generated. Different types of sensor faults are simulated through a manipulation of one sensor node by

a) substituting the sensor readings with randomized values
b) rotating the sensor node by 45°
c) shifting the sensor node by 20 cm

The topology of the ANNs is optimized according to three criteria: prediction accuracy, ability of sensor fault detection, and time consumption during training. To optimize the topology, various numbers of hidden layers and hidden neurons per layer are tested. Interlayer connections, allowing only synapses between neurons in adjacent layers, as well as supralayer connections, allowing synapses between neurons in distant layers, are applied. As for the neuron behaviors, different training algorithms, backpropagation [11] and resilient backpropagation [12], are tested. The training and testing of each type of fault is repeated five times. As a perfomance measure, the root mean square errors (RMSEs) between the measured and the predicted data are calculated and averaged for all repetitions.

3.3 Test results

The efficiency of sensor fault detection depends on the increases of the RMSEs between the measured and the predicted magnitude of the sensor node. Benchmarks for different neural network topologies are shown in Table 1. For non-faulty sensor data, small RMSEs indicate a good approximation. The smallest RMSEs between 0.063 and 0.144, representing the best results, are retrieved with interlayer connected topologies and backward propagation. Using topologies with supralayer connections or the resilient backpropagation training algorithm leads to RMSEs between 0.132 and 0.208. When propagating data of simulated sensor faults through the ANNs, increased RMSE indicate efficient sensor fault detection. The RMSEs of all ANNs increase by a factor of 1.5 to 12 for different simulated sensor faults. Run times during training deviate by a factor of up to 40 between 4.6 s and 172.4 s. In general, the time increases with the number of hidden neurons within an ANN. Using resilient backpropagation, compared to backpropagation, increases the training time considerably by a factor of around 6 for identical topologies.

By comparing the benchmarks of different ANN topologies and taking all criteria and results into consideration, a 3-2-1 interlayer-connected ANN with backpropagation is concluded to be most appropriate for the test structure Figure 4. The results are marked bold in Table 1. The RMSE of 0.102 for the test data is within the lower third of all results. With respect to the simulated sensor faults, the RMSEs of 0.807, 0.603, and 0.410 for randomizing, rotating, and shifting the sensor nodes are within the top quarter of all results. These RMSEs correlate with relative errors of 30.05 %, 27.78 %, and 18.87 % respectively. The training of the 3-2-1 topology, executed in 13 s, was the second fasted.

Table 1: Arithmetic mean of root mean square errors during training and fault detection, and time consumed during training for several network topologies

			Simulated sensor faults			
	Topology	Testing	Random	Rotated	Shifted	Time [s]
Interlayer, backpropagation	3-1	0.149	0.767	0.612	0.334	6.6
	3-2-1	**0.102**	**0.807**	**0.603**	**0.410**	**13.0**
	3-3-1	0.144	0.751	0.581	0.283	17.2
	3-5-1	0.081	0.784	0.597	0.370	25.0
	3-7-1	0.063	0.756	0.587	0.294	32.2
	3-2-2-1	0.092	0.813	0.625	0.432	21.0
	3-5-5-1	0.137	1.213	0.752	0.938	46.6
Interlayer and supralayer, backpropagation	3-3-1	0.147	0.762	0.593	0.317	15.2
	3-5-1	0.132	0.764	0.600	0.324	22.6
	3-2-2-1	0.137	0.760	0.601	0.312	19.4
interlayer, resilient backpropagation	3-3-1	0.153	0.783	0.610	0.364	113.0
	3-5-1	0.143	0.729	0.598	0.249	172.4
	3-2-2-1	0.208	0.744	0.607	0.282	120.6

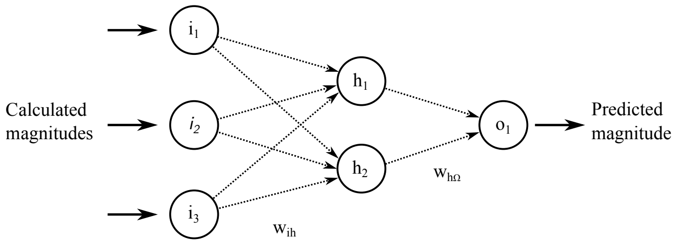

Figure 4: Optimal ANN topology for sensor fault detection: 3-3-1 feedforward neural network with unidirectional interlayer synapses

4 SUMMARY AND CONCLUSIONS

This paper has presented a decentralized autonomous sensor fault detection strategy for wireless structural health monitoring systems based on artificial neural networks. Autonomous sensor fault detection has been implemented by embedding artificial neural networks into the sensor nodes. The ANNs have been trained to predict expected sensor data to be compared to measured sensor data in order to detect sensor faults. To verify the proposed approach, the SHM system has been installed on a test structure for validating tests. Several different network models have been tested to identify an efficient, resource-saving configuration. As a result, an artificial neural network with 3-2-1 interconnected topology and backpropagation training algorithm training has been proven to be the optimal solution for the structure tested in this study. In summary, it can be concluded that sensor fault detection using neural networks can improve the dependability and the accuracy of structural health monitoring systems.

In future work, different types of artificial neural networks and further topologies may be investigated. The SHM system may be tested under varying conditions on test structures with other stimuli or on site. To ensure portability of the proposed fault detection approach, the SHM system may be implemented on other types of sensor nodes.

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